

Simulating Flight Routing Network Responses to Airport Capacity Constraints in the US

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This paper presents a model which simulates changes in the airline system flight routing network under alternative policy scenarios. The model simulates a game between airlines, in which each airline increases flight frequency in order to maximize its own profit. The underlying modeling framework allows the relationships between changes in fares, passenger demand, infrastructure capacity constraints, flight delays, flight frequencies, and routing network to be simulated. The model is validated for a network of airports in the United States in 2005, before being applied to simulate changes in the same network through 2030 under two policy scenarios. Both scenarios limit airport capacity expansion: (i) in the whole system, and (ii) at Chicago O'Hare International, a primary hub airport, only. Simulated passenger demand, air traffic, flight delays, system CO₂ emissions and Chicago O'Hare NO_x emissions are compared to a baseline scenario in which airport capacity is expanded as planned by the FAA. Despite a significant impact on flight delays, the results show little impact of airport capacity constraints on system passenger demand, air traffic growth or CO₂ emissions, but show a shift of connecting traffic away from congested hub airports at which capacity is limited to other less congested hub airports, thus reducing traffic growth at these congested airports, and reducing the growth in NO_x emissions.

I. Introduction

WORLDWIDE demand for air travel has shown significant growth over the past five decades. Between 1960 and 2005 worldwide scheduled passenger air travel grew from 109 billion passenger-km travelled to 3.7 trillion – an average growth rate of over 8% per year [1,2]. Forecasts for future growth are also high – the Airbus Global Market Forecast from 2007 to 2026 [3] and the Boeing Current Market Outlook from 2006 to 2026 [4] both predict growth rates of around 5% per year. By 2050 conservative estimates predict a 30-110% growth in passenger kilometres travelled over 2005 levels [5], while more aggressive estimates predict an increase of an order of magnitude [6]. Associated with such growth in demand for air travel is a growth in air traffic (number of aircraft movements) to serve that demand, as modeled by Hancox and Lowe [7], Bhadra et al. [8,9], and Reynolds et al. [10]. This growth in air traffic is expected to produce a significant environmental impact, as reported by the Intergovernmental Panel on Climate Change (IPCC) [1] and Cairns et al. [11], including air quality and noise impacts, and global climate change.

Growth in air traffic is already constrained by environmental restrictions (particularly noise). An emerging constraint is air traffic system capacity, given widespread local community resistance and environmental restrictions to airport capacity expansion. Airport and airspace capacity already constrain flight operations at many major airports in the United States [12], Europe [13], and other regions. Reynolds et al. [10] illustrates that if airlines continue to increase air traffic to match the projected growth in demand, without changes in flight network routing or the sizes of aircraft operated, as modeled by existing studies examining the environmental impacts of aviation [10,14,15], average arrival delays would be unrealistically high. Instead, as suggested by Kostiuik et al. [16] and Reynolds et al. [10], such delays are unlikely to occur in reality as airlines would adjust the way in which they operate in order to reduce the negative impacts of flight delays on cost and passenger demand, in order to maximise their profit.

Long et al. [17] suggests that airline responses to delay may include avoiding congested hubs, using secondary airports, moving flights to off-peak times, broadening the range of departure times, and reducing flight frequency while increasing aircraft size. As demonstrated by Reynolds et al. [10] and Evans et al. [18], passengers may also

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respond to the increased travel times and costs associated with delays. Evans et al. [18] and Elhedhli and Hu [19] demonstrate explicitly that airport capacity constraints have an impact on optimal airline network routing. Depending on airport capacity expansion in the future, airline responses to airport capacity constraints are thus likely to alter the structure of future air traffic growth, in turn affecting the environmental impact of aviation. Local air quality and noise may be particularly impacted, because, if an airline chooses to shift its hub operations away from a congested hub airport or airport within a multi-airport system to a less congested airport in order to reduce costs, the local air quality and noise levels at both the airport from which traffic was moved, and at the airport to which the traffic was moved, may change significantly. In order to generate a plausible forecast of air traffic growth in a capacity constrained system, and to identify its environmental impact, it is therefore essential to quantify the degree to which passengers and airlines are likely to respond to capacity constraints.

Evans et al. [18] describes an integrated flight routing and scheduling model to predict changes in passenger demand, fares, flight frequencies, and airline routing under airport capacity constraints, and demonstrates its application on a series of simple theoretical networks. This paper extends the model described by Evans et al. [18], by explicitly modeling airline competition by simulating a game between airlines, improving the accuracy of the model significantly. The modeling approach is described in Section II. The model is then validated by comparing model results for a network of 14 cities and 22 airports in the United States in 2005 to observed data, presented in Section III. In Section IV, the model is applied to simulate changes in flight routing for this same network through 2030 under alternative airport capacity scenarios. Three scenarios are examined: a baseline case in which airport capacity is expanded according to existing capacity expansion plans; a “no capacity expansion” case in which capacity is not expanded at any airports in the system; and a “no ORD capacity expansion” case in which capacity is expanded at all airports except a key hub airport for two major airlines – Chicago O’Hare airport (ORD). Conclusions are presented in Section V.

II. Modeling Approach

Evans et al. [18] describes an approach to model airline network routing under airport capacity constraints. The approach integrates models of passenger demand, airline competition, flight delay and airline cost, allowing the impact of constraints (in this case airport capacity) to be examined on flight delays, fares, flight frequencies, and routing networks. This approach is modified and extended in this paper to more realistically model airline network routing, and to simulate changes in routing networks under changing airport capacity constraints.

Evans et al. [18] applies an airline routing and scheduling model which is based on maximisation of system profit, as opposed to individual airline profit, to optimise flight frequencies and routing, similar to the approach used by Harsha [20]. In order to model the effects of frequency competition between airlines, which can be observed to increase flight frequencies between city pairs well above the level that maximizes system profit (system optimal), Evans et al. [18] constrain the objective function to serve a true origin-ultimate destination (O-D) flight frequency between each city pairs calculated by an integrated airline competition model. The resulting frequency, however, under-predicts observed flight frequencies (on average by 34% [18]). In reality, each airline operating within a system maximizes its own profit, subject to the flight frequencies (and fares) it observes from its competitors. Airlines are able to increase market share by increasing flight frequency – frequency competition, as described by Schipper et al. [21]. However, each airline responds in the same way, and as described by game theory, flight frequencies increase well above the system optimal levels. The system settles to an equilibrium when the marginal cost of adding a flight is greater than the marginal revenue obtained from the increased market share gained by adding the flight. Accordingly, a more representative model of the system can be developed by simulating a game between different airlines, in which each airline maximises its own profit. This is the approach employed in this paper.

Schipper et al. [21] and Carlsson [22] describe how airlines compete by fare and flight frequency, and analytically solve a two stage game in which airlines simultaneously choose flight frequencies in the first stage of the game, and in the second stage, after having observed the other airlines’ chosen frequencies, the airlines simultaneously choose fares. In this paper only the first stage of the game – when flight frequencies are chosen – is solved by simulating a game. The second stage – the choice of fares – is solved using a separate fare model.

The modeling framework is described in Figure 1. The simulation of the game (solved by iteration) is integrated into this framework, and is described for two airlines in Figure 1 (two airlines are illustrated for simplicity – the game can be solved for any number of airlines greater than one). The figure is followed by descriptions of the framework, each sub-model presented, and the iteration solution of the framework.

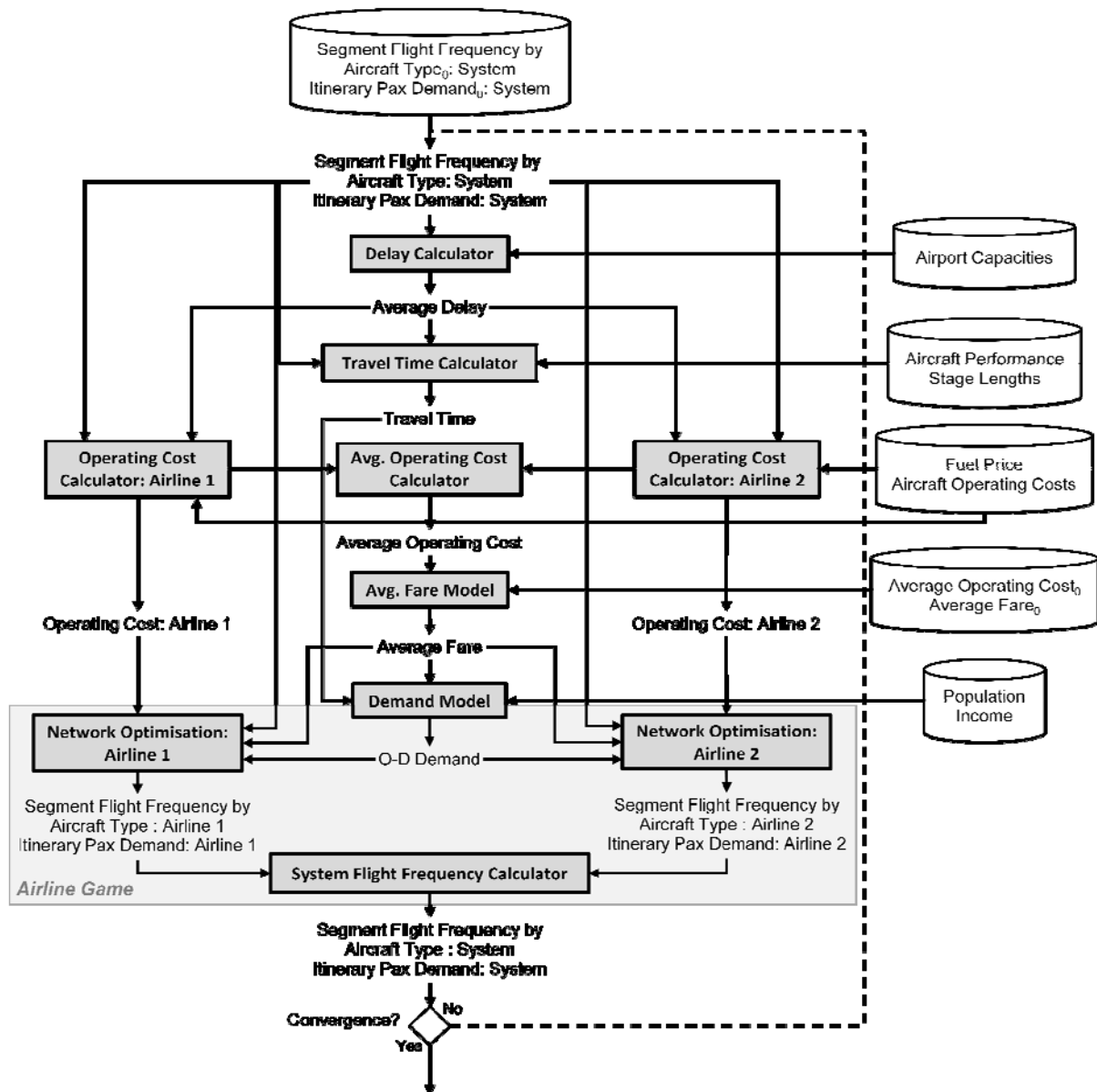


Figure 1. Modeling Framework: Airline Network Routing Response Model

With an initial estimate of flight frequencies per day for each aircraft type by flight segment for the entire network modeled, average flight delays at each airport are estimated using a *Delay Calculator*, utilizing specified airport capacities. Operating costs for each airline modeled are estimated using an *Operating Cost Calculator*, as a function of aircraft types operated on each segment, passenger demand served (from an initial estimate of itinerary passenger demand served), flight delays, and specified fuel and aircraft operating costs by airline. Average O-D travel time for each city pair market modeled is calculated using a *Travel Time Calculator* as a function of flight delay, aircraft types operated, passenger itinerary demand served (providing information about passenger routing), specified aircraft performance characteristics (such as cruise speed) and stage length information.

Average O-D operating costs by city pair, across all airlines, are calculated using an *Average Operating Cost Calculator* which outputs average O-D operating costs to an *Average Fare Model*. This model estimates average O-D fares by city pair, across all airlines (fares are not calculated for each airline separately), as a function of average operating costs and system flight frequency information, both by O-D city pair (including non-stop and connecting flights). Average fares are output to a *Passenger Demand Model*. Along with average travel times from the *Travel*

Time Calculator, specified population and income data, the *Passenger Demand Model* estimates available O-D passenger demand for each city pair modeled.

Each airline's segment flight frequencies, passenger routing from origin to destination, and aircraft operated, are simulated using a *Network Optimization Model*, which is solved iteratively with a *System Flight Frequency Calculator* that calculates total flight frequency offered by all airlines for each city pair, required to estimate airline market share. A game theoretical equilibrium between airlines is reached when the system reaches convergence, modeling the effects of airline competition. Because the *Delay Model*, *Travel Time Calculator*, *Operating Cost Model*, *Average Operating Cost Model*, *Average Fare Model*, and *Passenger Demand Model* are not integrated within the network optimization, they must also be updated as segment flight frequencies and itinerary passenger demand is re-estimated by the *Network Optimization Models*. These models are therefore included in the iteration loop that is required to identify the game theoretical equilibrium.

Each of the sub-models shown in Figure 1 is described in greater details in the sections below.

A. Modeling Flight Delay

The impact of airport capacity constraints on airline cost and passenger travel time is modeled using a rapid airport delay model as by Evans et al. [18], and described in detail by Evans [23]. In this model flight delays, both on the ground and in the air, are estimated as a function of flight frequencies and airport capacity constraints, and are added to gate departure delays due to mechanical failures and late arrivals, which are assumed to remain at current levels (this assumes that schedule padding increases to maintain schedule reliability). Delays due to airport capacity constraints are estimated using queuing theory, applying the cumulative diagram approach and classical steady state simplifications described by de Neufville and Odoni [24]. Runway departure delays are distributed between the taxiway and gate according to a taxi-out threshold calculated for each airport from historical delay data. Similarly, delays due to destination airport capacity constraints are distributed between the air and ground according to an airborne holding threshold calculated for each airport from historical delay data, and above which delay is assumed to be propagated upstream to the departure gate. The delays estimated by this model increase passenger travel time and airline operating costs, as calculated by the *Operating Cost Calculator*.

B. Modeling Passenger Travel Time

Average passenger O-D travel time for each city-pair modeled is calculated by averaging O-D travel times for each passenger travelling between that city-pair, based on segment travel times on all the flight segments used, including both non-stop and connecting itineraries. Only connecting itineraries with a single connection are considered, with hubs limited to those operated by the airline serving that passenger.

Travel time for each flight segment is calculated as a function of unimpeded (delay-free) flight time by aircraft type. These are estimated according to the Base of Aircraft Data (BADA) [25], the Aircraft Engine Emissions Databank [26], and average airport arrival and departure delays by origin and destination airport (from Airline Service Performance Metrics (ASPM) database [12]).

C. Modeling Airline Operating Costs

Airline costs modeled include aircraft operating costs, aircraft servicing costs, traffic servicing costs, passenger servicing costs, reservation and sales costs, and other indirect and system overhead costs, as suggested by Belobaba [27]. Aircraft operating costs include fuel and oil costs, crew costs, maintenance costs, aircraft rental, depreciation and amortization costs, and landing fees. With the exception of fuel and oil costs and landing fees these costs are input directly from US Department of Transport (DOT) Form41 data [28]. Fuel costs are calculated independently as a function of fuel prices from Air Transport Association (ATA) data [29], and aircraft fuel burn in each flight phase, estimated according to BADA [25] and the Aircraft Engine Emissions Databank [26]. Landing fees are input from the International Air Transport Association's (IATA) Airport and Air Navigation Changes Manual [30].

All other costs are input directly from US DOT Form41 data [28]. These include aircraft servicing costs, covering handling aircraft on the ground and landing fees; traffic servicing costs, covering the processing of passengers, baggage and cargo at airports; passenger servicing costs, covering meals, flight attendants and in-flight services; reservation and sales costs, covering airline reservations and ticket offices, including travel agency commissions; and other indirect and system overhead costs, covering advertising and publicity expenses and general and administrative expenses.

Airline costs are modeled per flight and per passenger, as required by the *Network Optimization* and *Average Fare Models* described below. Costs per flight include all aircraft operating costs and aircraft servicing costs, with the exception of the proportion of the fuel burn that can be attributed directly to passengers. This fuel burn, along

with traffic servicing costs, passenger servicing costs, reservations and sales costs, and other indirect and system overhead costs are modeled per passenger.

D. Modeling Fares

The modeling approach adopted for modeling fares is to adjust base year average fares to maintain the base year rate of return. This is identical to the approach used by Waitz et al. [31], and is accomplished by maintaining a proportional relationship between fares and costs (by true origin-ultimate destination). Thus, any percentage change over base year O-D cost is applied directly to average base year fares. The approach is simple and transparent, but also has the advantage of modifying existing fares, and therefore implicitly capturing elements of all constraints driving fare pricing, and not just those modeled. This is essential because, as described by Belobaba [32], airlines do not simply apply cost-based pricing, but apply a combination of cost-, demand-, and service-based pricing, applying price discrimination and product differentiation to increase total flight revenues.

E. Modeling Passenger Demand

O-D passenger demand between cities i and j is modeled using a simple one-equation gravity-type model, as applied by Reynolds et al. [10] and Evans et al. [18]:

$$D_{ij} = (P_i P_j)^\alpha (I_i I_j)^\gamma e^{\delta A_{ij}} e^{\theta B_{ij}} (Fare_{i,j} + \theta \cdot T_{i,j})^{-\tau} \quad (1)$$

where P is the greater metropolitan area or equivalent population; I is the associated greater metropolitan area per capita income; A and B are binary variables indicating whether one or both cities in the pair have qualities which might increase visitor numbers (e.g. a major tourist destination or capital city); $Fare$ is passenger airfare between the cities averaged over all itineraries; θ is the passenger value of travel time; T is the travel time between the cities averaged over all itineraries; and the exponents give the elasticity of demand to each of the explanatory variables (i.e. % change in demand resulting from a % change in each explanatory variable). The final expression in brackets represents the generalized cost to a passenger of air travel between the cities, and it is through this expression that it is possible to include the demand-reducing effect of increased fares as well as that of increased travel time. Using demand data for the United States in 2005 [28,33,34], the coefficients (exponents) in equation 1 are estimated separately for short-haul, medium-haul and long-haul journeys. All estimated coefficients are significant at the 95% confidence level, with R^2 values ranging from 0.56 to 0.76. Passenger value of time was derived from data from the US Department of Transport [35], adjusted to 2005 dollars.

The model described in equation 1 does not capture some passenger demand effects that are significant in some world regions, such as passenger mode choice. This simplification is, however, necessary for the computational efficiency required of the model for integration in the framework presented in Figure 1.

F. Airline Network Optimization

Profit maximization using a large scale linear programming approach is applied to model individual airline network routing, frequency, and fleet (aircraft sizes operated) responses to changes in cost, demand, and fares. This optimization is solved separately for a series of airlines within an iterative scheme simulating convergence to a game theoretical equilibrium, capturing the effects of competition between airlines. The airline objective function is presented in equation 2 below.

$$\max \left(\sum_{i,j} \sum_{p \in P_{i,j}} Fare_{i,j} \cdot Pax_{i,j,p} - \sum_{m,n,k} Cost_{fl_{m,n,k}} \cdot Fltfreq_{m,n,k} - \sum_{i,j} \sum_{p \in P_{i,j}} Cost_{pax_{i,j}} \cdot Pax_{i,j,p} \right) \quad (2)$$

where $Fare_{i,j}$ represents the average fare between O-D city pair i and j ; $Pax_{i,j,p}$ represents passenger demand between O-D city pair i and j , on itinerary p ; $Cost_{fl_{m,n,k}}$ represents average cost per flight on the flight segment between airports m and n , for aircraft type k ; $Fltfreq_{m,n,k}$ represents average number of flights per day on the flight segment between airports m and n , using aircraft type k ; and $Cost_{pax_{i,j}}$ represents average cost per passenger between O-D city pair i and j . Cities i and j are served by one or more airports m and n respectively.

The decision variables in the optimization are passenger itinerary demand ($Pax_{i,j,p}$) and segment flight frequency ($Fltfreq_{m,n,k}$), which incorporate information to completely describe the airline flight routing network, schedule (only to the level of daily frequency), fleet, and passenger itinerary routing.

The objective function is constrained by a system of linear equations describing airline routing and scheduling requirements and limitations, including a demand constraint, a seat constraint, and an airport balance constraint. The demand constraint is described by equation 3:

$$\sum_{p \in P_{i,j}} Pax_{i,j,p,a} = \left(\frac{Fltfreq_{i,j,a}}{\sum_{a \in A} Fltfreq_{i,j,a}} \right) \cdot D_{i,j} \quad (3)$$

where $Pax_{i,j,p,a}$ represents passenger demand between O-D city pair i and j , on itinerary p , for airline a ; $Fltfreq_{i,j,a}$ represents the airline O-D flight frequency, including non-stop and connecting flights, between city i and j , for airline a ; and $D_{i,j}$ represents the available demand between city i and j , as estimated by the demand model described above. The term in brackets is an estimate of the market share captured by airline a , suggested as a rule-of-thumb by Belobaba [32]. This formulation is non-linear, and is therefore linearized and the flight frequency of all other airlines updated each iteration of the game described below.

The seat constraint applied to the optimization limits the number of passengers served on each flight segment to be less than or equal to the number of seats available, as described in equation 4:

$$Pax_{m,n,k} \leq LF_{max} \cdot Seats_{m,n,k} \quad (4)$$

where $Pax_{m,n,k}$ represents passengers flown between airports m and n (i.e. by flight segment), on aircraft type k ; LF_{max} represents a maximum average load factor permitted (such as 95%); and $Seats_{m,n,k}$ is the number of seats offered by the airline between airport m and airport n , on aircraft type k . The number of seats offered by the airline ($Seats_{m,n,k}$) is a direct function of the aircraft seating capacity (type specific) and the flight frequency offered.

The airport balance constraint applied to the optimization limits the number of flights of each aircraft type departing from an airport per day to equal the number of flights of that aircraft type arriving, and vice versa, as described in equation 5:

$$\sum_{n \in N} Fltfreq_{m,n,k} \leq \sum_{n \in N} Fltfreq_{n,m,k} \quad (5)$$

G. Iterative Framework

The integrated framework presented in Figure 1 is solved by iteration. This iterative approach is designed to simulate system convergence to a game theoretical equilibrium between airlines, while simultaneously updating the operating costs, available passenger demand, and fares inputs for the network optimizations for each airline, which are functions of flight delay and passenger travel time, which must also be updated.

The airline game is simulated by updating the flight frequencies offered by all airlines, according to the outputs of each airline network optimization. These flight frequencies are inputs to the market share formulation within the demand constraint within each network optimization, and allows the gaming effect to be simulated whereby each airline may increase its frequency in order to capture more market share, but whereby each airline's market share is not increased to the degree expected because of the simultaneous increase in frequencies offered by the other airlines. An airline no longer increases frequency when the marginal increase in revenue resulting from the addition of another flight is smaller than its marginal cost. The system reaches the game theoretical equilibrium when all airlines reach this equilibrium on all markets. Since airlines experience different operating costs, those with the lowest costs can add more extra flights and thus gain more market share.

III. Model Validation

The model was validated by reproducing the 2005 airline network routing, flight frequency, and fleet choice in the United States. The network of cities and airports modeled includes 5 airlines, operating between 22 airports[‡], and serving 14 cities[§]. This airport set served approximately 75% of scheduled flights in the domestic US in 2005 [36]. The number of airlines, airports and cities modeled is limited in order to maintain model tractability. The airlines modeled represent those with greatest market share serving the modelled city set. Each airline is constrained to operate hubs as operated in 2005, and serve only those airports within the airport set served in 2005. Three aircraft types (small, medium and large), and two age categories (certified before and after 1995) are modeled, applying

[‡] Chicago O'Hare (ORD), Chicago Midway (MDW), Atlanta (ATL), Dallas-Fort Worth (DFW), Dallas Love (DAL), Los Angeles (LAX), Ontario (ONT), Houston International (IAH), Houston Hobby (HOU), Denver (DEN), Detroit (DTW), Philadelphia (PHL), Newark (EWR), New York Kennedy (JFK), New York LaGuardia (LGA), Washington Dulles (IAD), Washington National (DCA), Boston (BOS), Miami (MIA), San Francisco (SFO), Oakland (OAK), and Seattle Tacoma (SEA).

[§] New York City, Chicago, Atlanta, Washington, Los Angeles, Dallas/Fort Worth, Houston, San Francisco, Miami, Denver, Detroit, Philadelphia, Boston, and Seattle.

aircraft performance data for representative aircraft in each category. All input data are consistent with the sources described in Section II.

It is noted that the airport set modeled also serves connecting O-D demand between cities not included in the city set. Each airline optimisation was constrained to serve an equal portion of this “extra-network” demand, ensuring that this demand is accounted for.

The flight frequencies identified by the model for the US domestic network described above are presented in Figure 2 for 2005. These results can be compared to observed flight frequencies for the network flown in 2005 [37], which is presented in Figure 3. A table summarizing the differences between the modeled and observed networks is presented in Table 1. This table presents differences between system passenger demand served, average fares offered, and system flight segment frequencies between airport pairs. R-squared values are presented for each of the metrics, comparing the modeled results to the observed values.

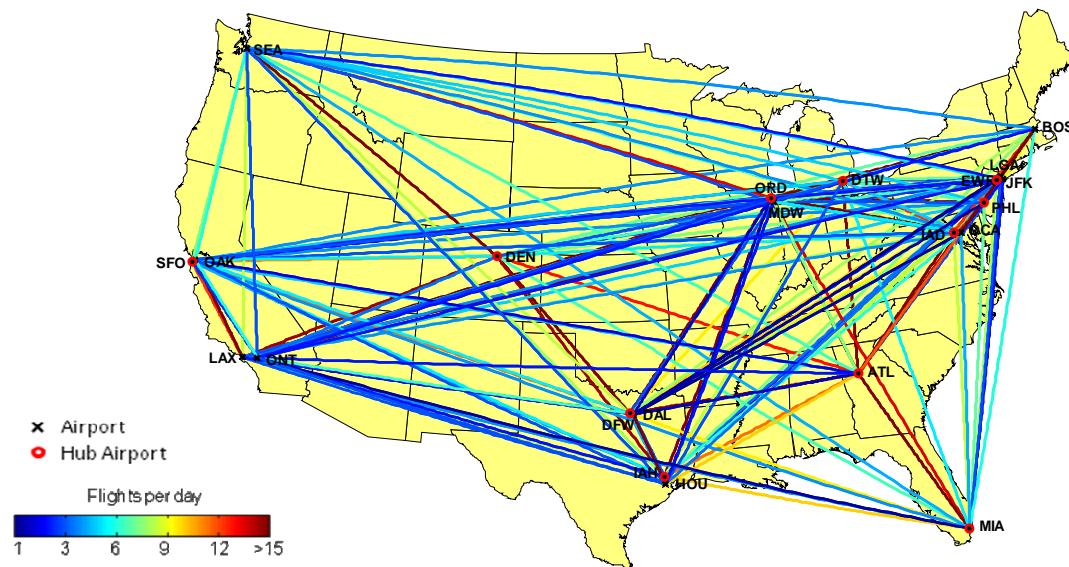


Figure 2. Simulated daily flight segment frequencies for US domestic network, 2005.

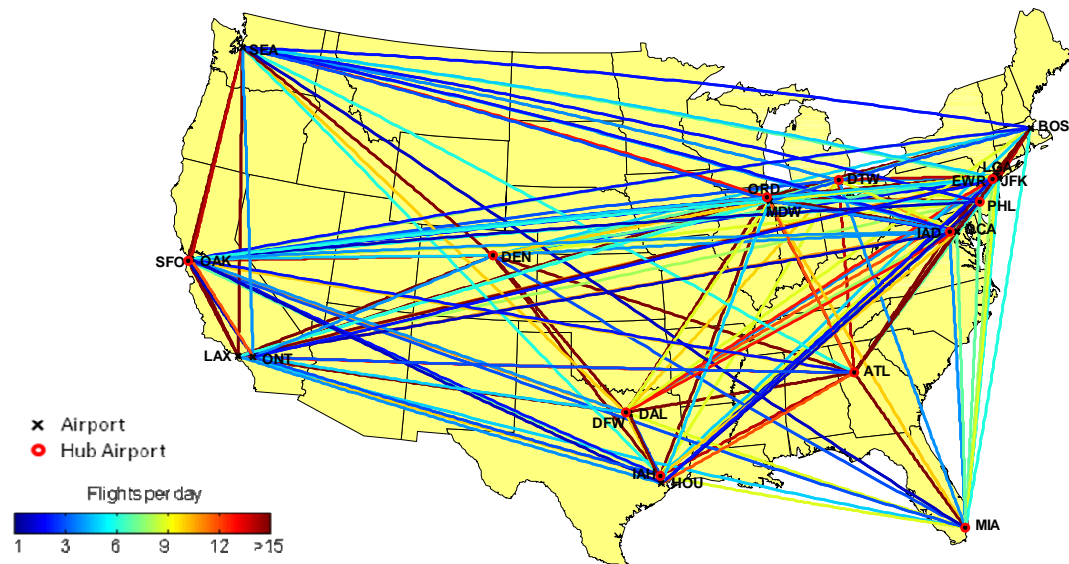


Figure 3. Observed daily flight segment frequencies for US domestic network, 2005.

Table 1. Model Results Comparison to Observed Data

| Passenger O-D Demand | | Fares | | Segment Flt Freq. | |
|----------------------|----------------|--------------|----------------|-------------------|----------------|
| % diff. System | R ² | Mean % diff. | R ² | % diff. System | R ² |
| 10% low | 0.509 | 11% high | 0.493 | 12% low | 0.777 |

The colors of the lines in Figure 2 and Figure 3 are close in most cases, indicating that the modeled frequencies are similar to the observed frequencies. The colors that differ generally indicate model under-prediction, which is supported by the results in Table 1.

In Table 1, passenger demand, summed over the modeled network, is 10% lower than the observed demand in 2005, and the R-squared comparing the two networks is slightly above 0.5, a value that is acceptable for cross sectional data. The slightly underestimated demand relative to the observed demand is explained by slightly overestimated fares – modeled fares are, on average, 11% higher than observed fares in 2005, with the R-squared between the values just under 0.5. Fares are a direct function of costs, implying that operating costs are overestimated by the model, as discussed below.

The modeled segment flight frequency, which is the most relevant metric defining aircraft emissions and thus environmental impact, is 12% lower than the observed data, with an R-squared between modeled frequencies and observed frequencies of nearly 0.78. The slightly underestimated flight frequency relative to the observed data corresponds to the underestimated passenger demand relative to the observed demand. Flight frequency is also affected, however, by the degree to which the airlines operate a hub-and-spoke network versus a point-to-point network. In the simulated network, 13.4% of passengers connect through a hub. This is just over double that in the observed data, where 5.8% of passengers connect. In the game simulation airlines are able to add frequency, and thus increase market share, by adding non-stop and connecting flights. Hub-and-spoke operations enable frequency to be added on more markets with fewer added flights than can be achieved through a point-to-point network. However, in reality, non-stop flights are more attractive to passengers than connecting flights, and airlines thus compete with frequency in the non-stop market specifically, as well as the O-D market (including non-stop and connecting flights) generally. This effect is not modelled, however, resulting in a higher percentage of connecting passengers in the simulated network, which reduces total flight frequency relative to observed data.

A further consequence of the greater use of hub-and-spoke operations in the simulated network than in the observed network is that the cost per passenger increases. Passengers travel greater distances per trip, requiring more fuel. This effect increases fares in the simulated network in comparison to observed fares in 2005, as described above.

The results presented in Table 1 suggest that the model described in this paper is indeed capable of capturing the main effects in airline choice of flight frequencies, fleet composition and flight routing network.

IV. Model Application

Air traffic growth and its environmental impact were simulated using the model described in Section II from 2005 to 2030 for the network of cities, airports and airlines for which the validation results are presented in Section III. A series of airport capacity scenarios were simulated. The model was run with population, income and oil price forecasts from the MIT Integrated Systems Model (IGSM) for the US Climate Change Science Program (CCSP) [38]. The IGSM is an integrated energy-economy-environment model with internally consistent population, income, and oil price scenarios. For the US it represents a relatively high growth scenario when compared to the other energy-economy-environment models run for the CCSP. Fleet fuel burn is assumed to decrease by 0.7% per year through the development of more fuel efficient technology, and its introduction into the fleet through historical trends in fleet turnover. This represents the average rate forecast by the Energy Information Administration to 2030 [39]. Three airport capacity scenarios are simulated:

- Case 1: *Baseline case*, in which airport capacity is expanded at all airports according to capacity expansion plans described by the US Department of Transport et al. [40] and airport specific sources [41,42,43].
- Case 2: *No capacity expansion case*, in which airport capacity is maintained at 2005 levels at all airports. Comparison of the results of this case to those of Case 1 allows the impacts of airport capacity expansion across the system to be examined.
- Case 3: *No ORD capacity expansion case*, in which airport capacity is increased at all airports according to capacity expansion plans described by the US Department of Transport et al. [40] and airport specific sources

[42,43], except at Chicago O’Hare International Airport (ORD), at which airport capacity is maintained at 2005 levels. Comparison of the results of this case to those of Case 2 allows the impacts of airport capacity expansion at a key hub airport to be examined.

Simulation results from 2005 to 2030 are presented in the figures below for each of the three cases. Figure 4 presents system-wide average arrival delay, passenger demand, operations and CO₂ emissions. Figure 5 presents average arrival delay, operations and airport NO_x emissions for ORD. Figure 6 presents the distribution of connecting passengers across the hubs operated within the system modelled, across all airlines.

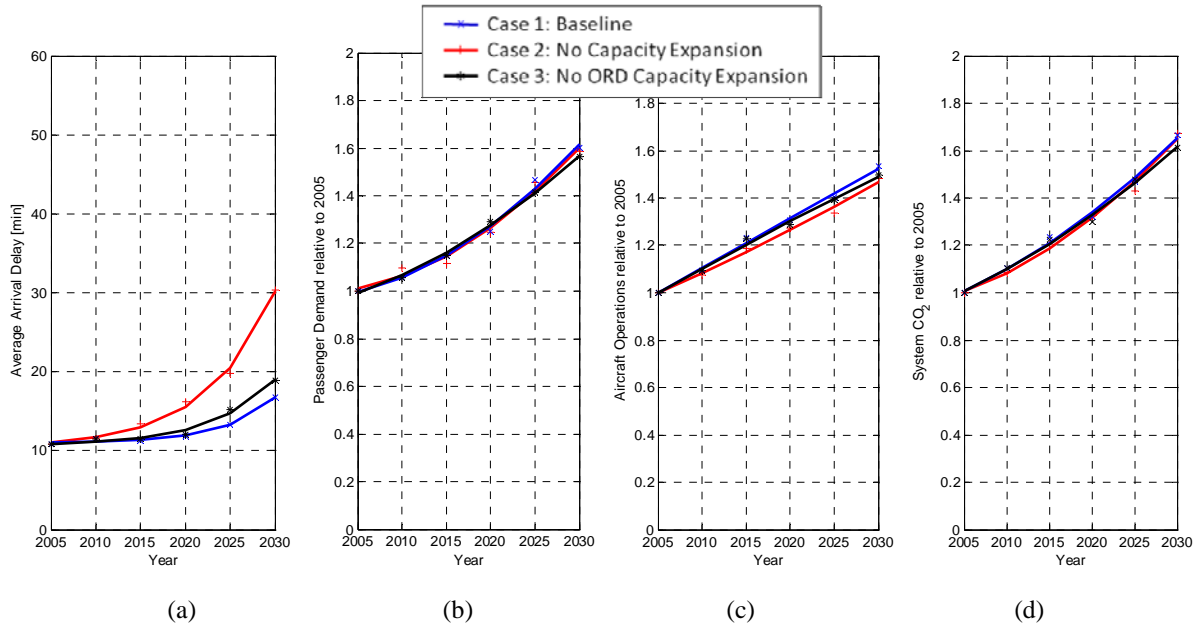


Figure 4. Simulated system a) average arrival delay, b) passenger demand, c) operations, and d) CO₂, from 2005 to 2030 for three airport capacity scenarios – Case 1: Baseline airport capacity expansion (blue), Case 2: No airport capacity expansion (red), and Case 3: No airport capacity expansion at Chicago O’Hare International Airport, but baseline airport capacity expansion at all other airports (black).

Figure 4 shows that, despite the significant impact of airport capacity constraints on flights delays (Figure 4a), the impact on system demand (Figure 4b), operations (Figure 4c) and CO₂ (Figure 4d) is small. The reason for this mitigated impact is partly the relatively small cost of flight delays to airlines. The majority of flight delay is incurred at the gate, where the aircraft is not running its engines, and therefore not burning fuel. The impact of flights delays on increasing fares is therefore small. The impact of the simulated flight delays on passenger demand is also small, primarily because travel times are generally long (average O-D passenger travel time in 2005 for the network modelled is just over 3 hrs) in comparison to the anticipated delay (at most, 30 minutes (Case 2 in 2030)), and the passenger value of time is comparatively low (US\$ 34/hr), imposing a relatively small extra cost of less than US\$ 8 per flight in Case 2 versus Case 1 in 2030, which compares to an average ticket price of US\$ 188.

Figure 4a indicate a significant impact of airport capacity constraints on average system arrival delay, with the delay in Case 2, where capacity is limited at all airports in the system, reaching nearly double the value reached in the baseline case, where airport capacity is added, by 2030. An average system arrival delay of 30 minutes would be higher than the average arrival delays at even the most congested airports in the system today. Even the reduced capacity in Case 3, where capacity is limited at ORD only, has an impact on average system arrival delay, increasing it by a few minutes over the baseline case by 2030.

The constrained capacity in Case 2, where capacity is limited at all airports in the system, does limit air traffic growth slightly, with the operations in 2030 being approximately 5% lower than in the baseline case, as shown in Figure 4c. The impact of the airport capacity constraints at ORD in Case 3 can also be seen, also limiting air traffic growth relative to the baseline case, although not to the degree of Case 2. The increasing operations in both Case 2 and 3 are accommodated despite the restricted airport capacity expansion by redistribution to other airports with available capacity. This is described in greater detail with reference to ORD below.

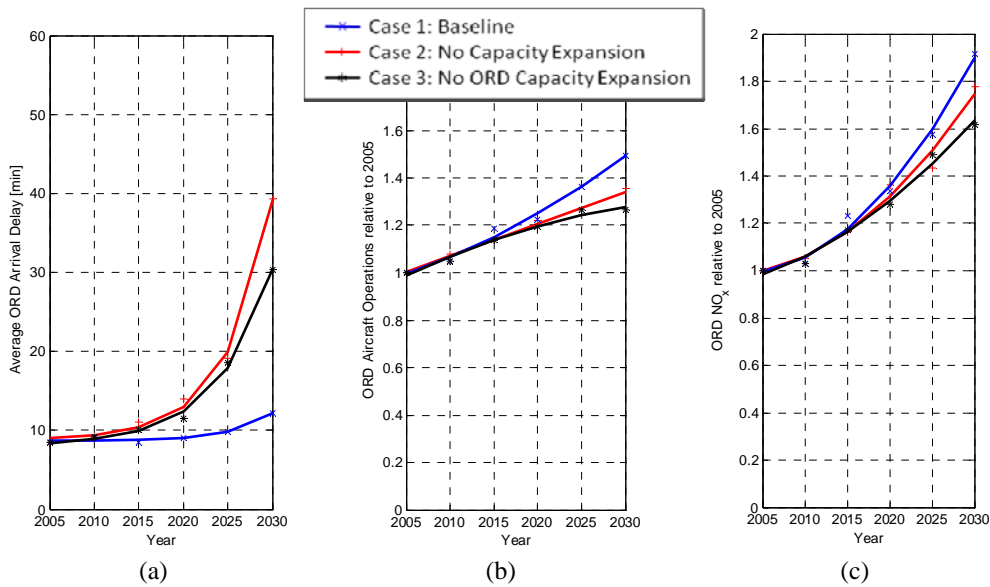


Figure 5. Simulated Chicago O’ Hare a) average arrival delay, b) operations, and c) NO_x, from 2005 to 2050 for three airport capacity scenarios – Case1: Baseline airport capacity expansion across the entire system (blue), Case 2: No airport capacity expansion across the entire system (red), and Case 3: No airport capacity expansion at Chicago O’Hare International Airport, but baseline airport capacity expansion at all other airports in the system (black).

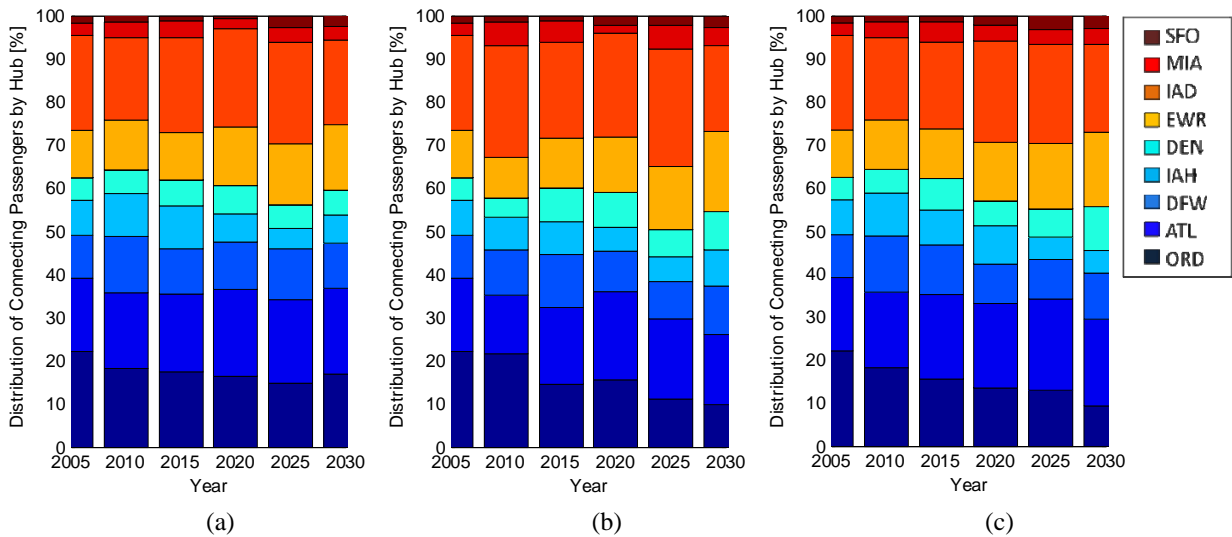


Figure 6. Connecting passenger distribution across system hubs from 2005 to 2050 for three airport capacity scenarios – a) Case1: Baseline airport capacity expansion, b) Case 2: No airport capacity expansion, and c) Case 3: No airport capacity expansion at Chicago O’Hare International Airport, but baseline airport capacity expansion at all other airports.

The impact of airport capacity constraints on airport specific traffic growth and network routing are more significant than for the system as a whole, as can be seen in Figure 5 and Figure 6. The impact of restricting airport capacity expansion at all airports (Case 2) results in congestion at ORD as well as the propagation of delay to the airport from other congested airports, increasing average airport arrival delays to nearly 40 minutes by 2030, as shown in Figure 5a. In Case 3, where there is only restricted airport capacity expansion at ORD, and not the rest of the system, the result is similar, with average airport arrival delays just over 30 minutes by 2030. This is in comparison to average arrival delays of under 15 minutes in the baseline case, in which ORD has a new runway operational by 2015, increasing the capacity from 190 ac/hr to 260 ac/hr.

The delays at ORD in Cases 2 and 3 could have a significant effect on flight routing. Figure 5b illustrates the simulated decrease in operations at ORD in Cases 2 and 3, where extra capacity is not available at the airport, relative to the baseline case, where it is assumed to become available. The decrease in operations at ORD in Cases 2 and 3 is despite the almost identical number of operations in the three cases across the whole system, shown in Figure 4c. The two airlines that operate hubs at ORD shift connecting traffic to other hubs airports. This is clear in Figure 6, where the percentage of connecting passengers at ORD (the lowest bar segment, in dark blue) decreases in Cases 2 (Figure 6b) and 3 (Figure 6c), but remains approximately constant in the baseline case (Figure 6a). The connecting traffic is shifted to other hubs operated by the airlines. It is also noted that the decrease in operations at ORD is higher in Case 3 than in Case 2 (Figure 5b). This is because in Case 2 there is less available capacity at the other hub airports to which to move the connecting traffic at ORD, because airport capacity expansion is limited at all airports. In Case 3, airport capacity expansion is only limited at ORD, so there is more available capacity at the other hub airports to which to move operations.

The impact of the routing network response to airport capacity constraints on the environment can be examined in Figure 5c, which plots airport NO_x emissions for the three cases. These results follow similar trends to the number of operations at ORD in Figure 5b, with the NO_x levels in Cases 2 and 3 being between 10% and 15% lower than in the baseline case. This decline is because of the reduction in traffic, indicating that, despite the increase in delays in these cases, and associated increase in NO_x emissions during taxi delays, the decrease in traffic has a dominating effect.

V. Conclusions

This paper presents a model that simulates changes in airline flight network routing under alternative policy scenarios, allowing passenger demand and air traffic growth to be simulated while accounting for the effects of airport capacity constraints to alter flight network routing. The model is validated by applying it to a network of 22 airports and 14 cities in the United States in 2005, with passenger demand, average fares, and segment flight frequencies being predicted within a 10-12% range compared to the observed values. The model developed is thus capable of capturing the main effects in airline choice of flight frequencies, fleet composition and flight routing network.

The model is applied to simulate operations in the same network of airports from 2005 to 2030 under two policy scenarios limiting airport capacity expansion, (i) in the whole system, and (ii) only at Chicago O'Hare International, a primary hub airport. Results are compared to a baseline case in which airport capacity is expanded as planned by the FAA. The simulation results suggest that airport capacity constraints may cause significant increases in average flight delay. Compared to a case where no capacity is added to the system, the average arrival delay in 2030 may be as high as 30 min, compared to 17 min for the baseline case (up from 11 min in 2005). However, despite the significant increase in arrival delays, the impact on system-wide passenger demand, air traffic growth, and CO_2 emissions is likely to be relatively small. The model simulations suggest that air traffic would be only 5% lower in 2030 in the case where no capacity is added compared to the baseline case, while reductions in passenger demand growth and CO_2 emissions are still smaller. The reason for this comparatively small decline is a redistribution of traffic from congested airports to other airports with more available capacity.

The impact of airport capacity constraints on congested hub airport traffic growth and local airport emissions is, however, more significant than on a system wide level, because of this shift in airline operations from congested airports to less congested airports. In the case where capacity expansion is limited at Chicago O'Hare International airport only, the simulation suggests that average arrival delays of 30 min would cause airlines operating the airport as a hub to shift as much as 40% of the connecting traffic at the airport in the baseline case to other hubs, reducing airport operations by 15% over the baseline case, and NO_x emissions by a similar amount. This result highlights the importance of modeling network routing responses to constraints when analyzing local airport traffic growth and emissions.

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